

Regresión Lineal simple

September 17, 2020

1 Regresión lineal simple

1.1 El paquete statsmodel para regresión lineal

```
[17]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
%matplotlib inline
```

```
[18]: data = pd.read_csv("D:\Rodolfo\Clases\Mineria\Advertising.csv")
```

```
[19]: data.head()
```

```
[19]:
```

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

```
[20]: lm = smf.ols(formula="Sales~TV",data = data).fit()
```

```
[21]: lm.params
```

```
[21]: Intercept    7.032594
TV             0.047537
dtype: float64
```

Modelo lineal predictivo : $\text{Sales} = 7.032594 + 0.047537 * \text{TV}$

```
[22]: lm.pvalues
```

```
[22]: Intercept    1.406300e-35
TV             1.467390e-42
dtype: float64
```

```
[23]: lm.rsquared
```

```
[23]: 0.611875050850071
```

```
[24]: lm.rsquared_adj
```

```
[24]: 0.6099148238341623
```

```
[26]: lm.summary()
```

```
[26]: <class 'statsmodels.iolib.summary.Summary'>
      """
                                OLS Regression Results
      =====
      Dep. Variable:                Sales    R-squared:                0.612
      Model:                        OLS      Adj. R-squared:            0.610
      Method:                      Least Squares    F-statistic:                312.1
      Date:                        Thu, 17 Sep 2020    Prob (F-statistic):          1.47e-42
      Time:                        09:48:48      Log-Likelihood:              -519.05
      No. Observations:              200      AIC:                        1042.
      Df Residuals:                  198      BIC:                        1049.
      Df Model:                      1
      Covariance Type:              nonrobust
      =====
                                coef    std err          t      P>|t|      [0.025    0.975]
      -----
      Intercept      7.0326      0.458      15.360      0.000      6.130      7.935
      TV              0.0475      0.003      17.668      0.000      0.042      0.053
      =====
      Omnibus:              0.531    Durbin-Watson:              1.935
      Prob(Omnibus):        0.767    Jarque-Bera (JB):            0.669
      Skew:                 -0.089    Prob(JB):                    0.716
      Kurtosis:             2.779    Cond. No.:                   338.
      =====

      Warnings:
      [1] Standard Errors assume that the covariance matrix of the errors is correctly
      specified.
      """
```

```
[27]: sales_pred = lm.predict(pd.DataFrame(data["TV"]))
      sales_pred
```

```
[27]: 0      17.970775
      1      9.147974
      2      7.850224
      3     14.234395
```

```

4      15.627218
...
195     8.848493
196    11.510545
197    15.446579
198    20.513985
199    18.065848
Length: 200, dtype: float64

```

```

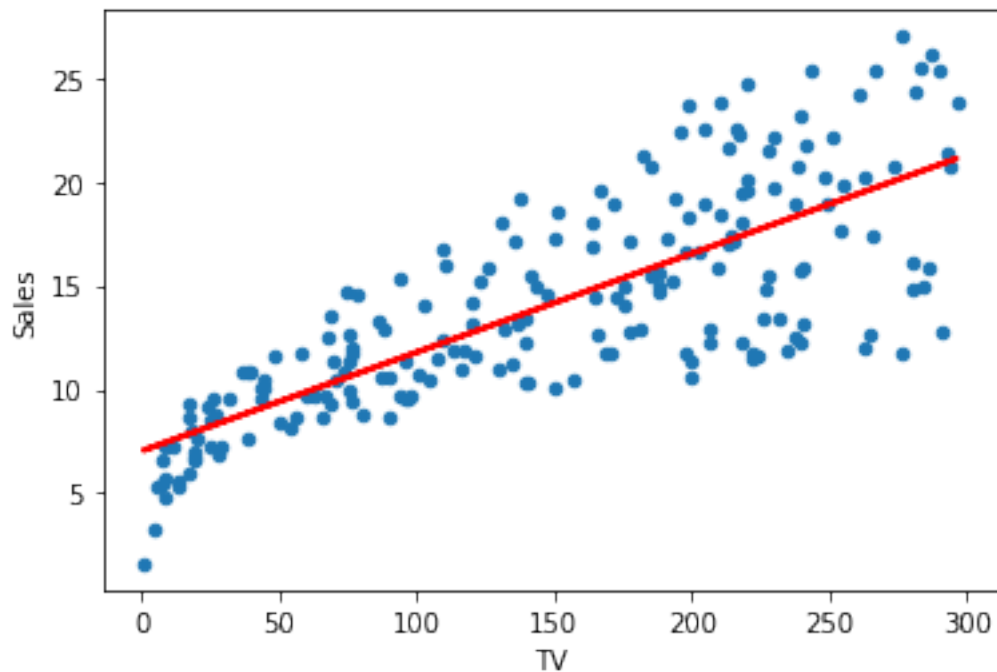
[28]: data.plot(kind = "scatter" ,x ="TV", y ="Sales")
plt.plot(pd.DataFrame(data["TV"]),sales_pred,c="red", linewidth=2)

```

```

[28]: [<matplotlib.lines.Line2D at 0x181d1ee1088>]

```



```

[29]: data["sales_pred"] = 7.032594 + 0.047537 * data["TV"]

```

```

[31]: data["RSE"] = (data["Sales"]-data["sales_pred"])**2

```

```

[35]: SSD = sum(data["RSE"])
SSD

```

```

[35]: 2102.5305838896525

```

```

[36]: RSE = np.sqrt(SSD/(len(data)-2))
RSE

```

```
[36]: 3.258656369238098
```

```
[37]: sales_m = np.mean(data["Sales"])  
sales_m
```

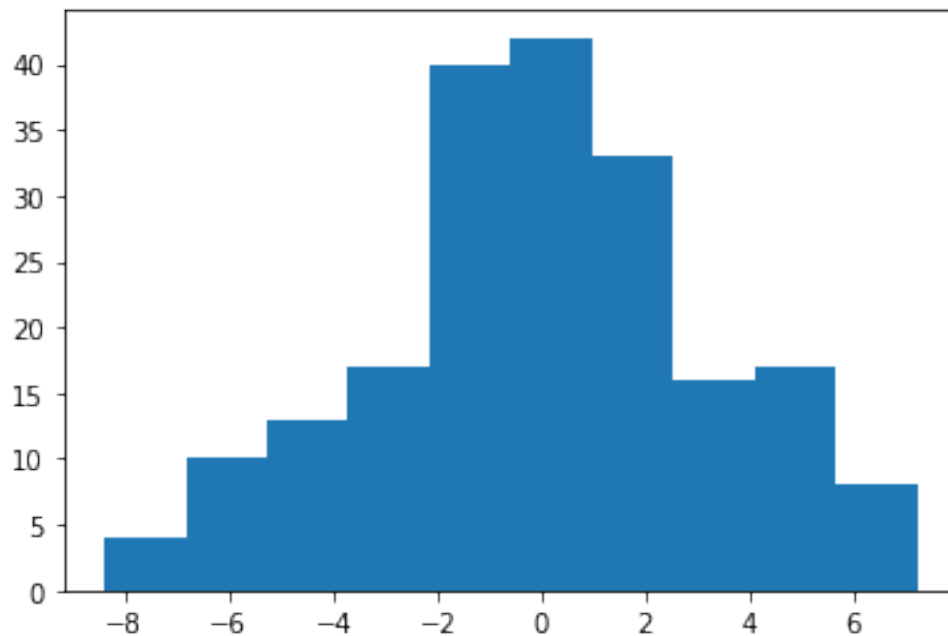
```
[37]: 14.022500000000003
```

```
[38]: RSE / sales_m
```

```
[38]: 0.2323876890168014
```

```
[39]: plt.hist((data["Sales"]-data["sales_pred"]))
```

```
[39]: (array([ 4., 10., 13., 17., 40., 42., 33., 16., 17.,  8.]),  
      array([-8.3860819 , -6.82624404, -5.26640618, -3.70656832, -2.14673046,  
            -0.5868926 ,  0.97294526,  2.53278312,  4.09262098,  5.65245884,  
            7.2122967 ]),  
      <a list of 10 Patch objects>)
```



```
[ ]:
```